Chapter 17
A Comprehensive Review of Machine Learning-Based Approaches to Detect Crop Diseases

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1 Introduction

Farming has developed to such a great level that it is simply not subject to feeding the ever-increasing population. However, this important source of revenue is under threat due to plant diseases. Plant diseases cause large-scale production and financial losses in farming and forestry, e.g., leaf rust (a fungal disease) in crops causes a considerable financial loss, and by eliminating only 20% of the disease, cultivators can leverage a profit of about ₹8761 crore. Consequently, detecting and identifying plant diseases early is of utmost significance to implementing on-time solutions [1]. There are multiple methods of detecting plant deformities. Some diseases have no visible symptoms or only appear when there is no reason to take measures. In such scenarios, conducting comprehensive analysis through a prevailing microscope is essential. In a few conditions, detection of symptoms is feasible only in portions of the electromagnetic spectrum that are invisible to human beings. However, most diseases produce some form of expression on the observable spectrum. Side effects of the infection should be visible on various portions of a plant, such as leaves, stems, fruit, and seeds [2].

Several studies have been done in the last few years on a variety of plant diseases using various image-processing techniques and deep learning-based models on distinct datasets. Several challenges were found while working with deep learning/machine learning models: nearly 80% of studies trained and evaluated their models using laboratory-conditioned datasets like the PlantVillage dataset [3]. The disease severity assessment is more significant than disease classification or diagnosis for the early identification and treatment of agricultural diseases in the field [4].

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The goal of the paper is to find and categorize plant infections based on the symptoms of diseases that show up on the leaves of the plant. In many instances, the diagnosis, or at the very least, the initial assessment of the ailment, is made by people through observation. Autonomous illness detection systems based on computer vision have already been presented by a number of researchers. Trained specialists may be skilled at diagnosing the disease. Unfortunately, there are generally no specialists in the field who can do data-based analysis and advice cultivators. Hence, it is very important to look for a swift, automated, inexpensive, and accurate methodology for detecting plant diseases.

1.1 Plant Disease Recognition and Classification

Computer vision, a branch of artificial intelligence, enables robots to replicate the human visual system and accurately analyze and identify real-world images just like humans do. Numerous industries, including medical diagnosis, espionage, satellite photography, and agribusiness, have already witnessed the advantages offered by computer vision-based solutions. In agriculture, computer vision-powered systems can effectively detect and categorize plant diseases by analyzing extracted disease characteristics or symptoms. These systems follow a well-defined sequence of steps, starting from image acquisition and progressing through various image-processing tasks such as scaling, filtering, segmentation, feature extraction, and selection. Ultimately, machine learning or deep learning techniques are employed for detection and classification purposes [5].

1.2 Plant Disease Causes

There are two primary groups of causes responsible for crop diseases: biotic and abiotic (Fig. 1). Biotic factors like viruses, fungi, bacteria, mites, and slugs cause microbial infections in plants, while abiotic factors like water, temperature, irradiation, and lack of nutrients hurt plant growth. But the present investigation is mainly confined to biotic factors (Fig. 2).

The three normal types of plant infections are discussed in the following manner:

i. **Viral diseases**: Among all plant contaminations trying to perceive and analyze sicknesses brought about by diseases is a tricky task. Likewise, these spots are frequently off track for side effects that happen because of the absence of sustenance or damage, as there is no prescient marker that can persistently screen the plants' state. The common spreaders of viral diseases are whiteflies, leafhoppers, aphids, cucumber-crawling insects, etc. [6].
ii. **Fungal diseases**: The main carrier of foliar diseases is a fungus, including rusts, rhizoctonia rots, sclerotinia rots, etc. [7]. It is primarily visible on long-standing

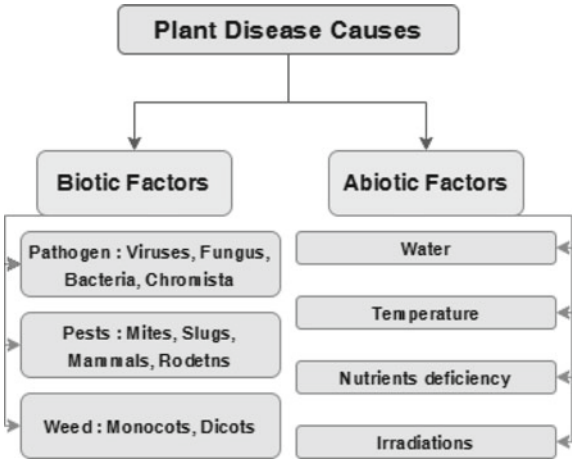

Fig. 1 Plant disease causes

Fig. 2 Different types of pathogens: viruses, fungi, and bacteria. *Source* Cotton Research Station, Sirsa

foliage with greyish marks or that is drenched in water. With the growth of the pest, these stains turn black and aid fungi to develop.

iii. **Bacterial diseases**: Although less frequent than fungi or viruses, pathogenic bacteria are the cause of numerous severe plant illnesses all over the world. However, bacterial infections do substantially less economic harm than fungi and viruses do [8]. Injury to plants is brought about by different microorganisms, bugs, and cultivating instruments during tasks like reaping and cropping.

1.3 Plant Disease Detection Based on Images

The photographs of leaves are an outstanding and abundant source of data on phytopathology and morphological behavior. Therefore, it is very worthwhile to extract and analyze such data thoroughly. Image processing makes a significant

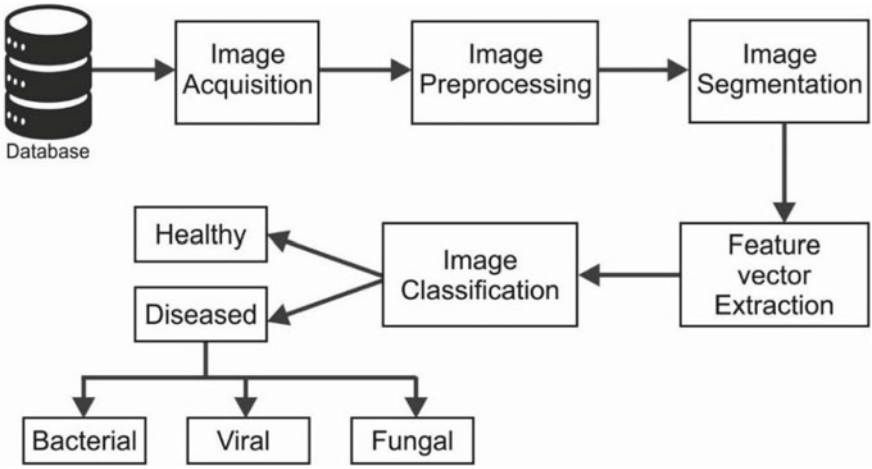

Fig. 3 Flowchart for disease detection

contribution to the detection and study of foliar disorders. Figure 3 depicts the process applied in the detection and classification of leaf disease. It gives an understanding of various methods used by researchers for disease detection through image processing and machine learning.

As shown in Fig. 3, the acquisition of photographs is the primary (first) step in disease detection. In most cases, photographs can be obtained from either a digital camera or an imaging framework. Since rough photographs include noise, it is necessary to remove these inaccuracies. Consequently, the next (second) step is called image preprocessing and consists of removing unnecessary distortions, along with contrast enhancement, to make image features clearer and brighter, e.g., the use of a Gaussian function that forms a soft blur is quite common to reduce noise in photographs. Next (third), image segmentation is the third step, which involves separating an image from its background, while the required area is segmented to highlight key attributes [9].

The fourth step that shows information and details about a picture is called "feature extraction." The leaf characteristics generally involve size, texture, and color, which are useful in the diagnosis of plants. Therefore, these selected attributes create an input attribute vector and are inserted into the classification system. This vector has the potential to distinguish one category of entities from another. Classification is the last step (fifth). It is worth noting that the selection of an appropriate classification architecture depends on the particular issue. The purpose of the classification system is to identify photographs by arranging them into several already defined classes on the premise of the resultant feature vector achieved in step 4. This is why there are two parts to the task of classification, which are called training and testing. The main purpose of training is to train the classification system on the training dataset. This means that the greater the quantity of in-process suites, the greater the accuracy rate.

It is important to note that the result, which shows whether the crop is healthy or sick based on the species name, should be found as quickly as possible.

1.4 Plant Disease Detection and Classification Algorithms

Fast advances in technologies used in mobile devices and digital cameras have enabled people to obtain digital photographs of crop plants and disease-carrying organs more conveniently. In the meantime, the use of machine learning and deep learning technologies has increased the viability of image processing and disease diagnosis, as shown in several studies. The frequently used approaches for plant infection detection and classification are elaborated below.

1.5 Machine Learning Approaches

Various machine learning algorithms, such as ANNs, decision trees, random forest, and SVMs, have been extensively applied in agricultural research. All these algorithms are described as follows [10].

Decision Tree: A decision tree is a nonparametric algorithmic scheme that divides the whole example space into equally limited and complete subsets (or levels) recursively. Every subgroup is portrayed by the set-up of choice guidelines that start its development, separating it from any remaining substitute. Decision trees are useful for both hierarchical and constant target variables. The DT algorithm has two major components: the selection criteria and the stopping rule. Misclassification error, the Gini index, or information entropy may be used to choose a target that is clear. The choice criterion is usually the least squared error for a constant target. Starting with all of the training data, DT looks for all of the predictive variables at all possible distant points to find the best separations that meet the selection criteria. This process goes on, repeating recursively until the withholding rules come into force. Since the DT is nonparametric, it does not assume the distribution and does not need a functional method for the predictors.

Random Forest: Decision trees are integrally unbalanced because a trivial alteration in the training dataset can largely affect the composition of the tree structure [10]. It is generally argued that the results of numerous trees can use volatility to detect more signals in the data than one tree can alone. Since RF is created from several architectures serving in performance, it is known as an ensemble framework. Not at all like one tree, RF attempts to show more vigor as it benefits from complex trees developed on disparate occurrences, which have been made significantly more arbitrary to relieve the effect of connection between tests or between trees.

Support Vector Machine: SVM linearly separates the mapped points on a high-dimensional space using hyperplanes. The collected data points, which are used to build such hyperplanes, are known as SVM (support vectors). This approach aims at

achieving the greatest margin data parting, which in itself has two goals: maximizing the minimal margin and separating the dependent variable from a hyperplane. The margin represents the distance between the hyperplane and perceptual objects. But sometimes, this is not possible or it is too hard to find the hyperplane that completely splits the answer. Consequently, softer hyperplanes are used rather than rigid hyperplanes to permit a smaller percentage of misclassification [11]. A higher-size attribute space is more expressive in nature. Nevertheless, if the size of the attribute space is larger than the number of perceptions, then providing the solution to an objective function will be complicated [11]. To deal with this, SVMs naturally use a kernel function, which employs kernel functions for mapping the data to an alternative attribute space in an implicit manner. This feature space can be described by having adequate knowledge of the pair-wise internal products of the perceptions in the data.

ANN: The two researchers named McCulloch and Pitts primarily developed ANN in 1943. ANNs were intended to imitate the neurophysiology of the human brain through the fusion of several simplified computation modules (otherwise known as perceptron, neurons, or nodes) into an extremely interlinked architecture. The single-hidden layer feed-forward network (SLFN) is a prominent form of the neural network system. It is adopted to analyze the neural network. The mathematical representation of SLFN can be given as:

$$y = G\left(a_0 + \sum_{j=1}^{h} a_j v_j\right) \tag{1}$$

$$v_j = F\left(\beta_{0j} + \sum_{i=1}^{k} \beta_{ij} x_i\right) \tag{2}$$

where x_i, $i = 1, \ldots, k$ and v_j, $j = 1, \ldots h$ represent the input units and the hidden units, respectively. The term β_{ij} denotes the weight of the like between the input-layer unit x_i and the hidden-layer unit v_j. Also, a_j signifies the connection's weight between the hidden-layer unit v_j and the output y. The bias of hidden-layer unit v_j is β_{0j} and the bias of the output y is a_0. $F(.)$ and, $G(.)$, respectively, indicate the unknown layer units' activation functions and output activation functions. Activation functions are often sigmoid functions: s-shaped functions like logistic and hyperbolic tangents that create limited values in the limit [0, 1] or [− 1, 1] [12].

1.6 Deep Learning Approaches

Deep learning (DL) techniques are a subset of machine learning (ML) techniques, which were initially developed in 1943. DL employs threshold logic to create computer models that closely resemble the observed biological pathways in humans. Numerous well-established DL models and frameworks have been developed for

image recognition, image segmentation, and image classification over the years. Below is a summary of several of these models:

Convolutional Neural Networks (CNN): Convolutional neural networks (CNNs) have a complex but highly effective architecture. Their architecture consists of several essential components. Input layer, convolution layer, pooling layer, entirely connected layer, and output layer are included. Combining the convolution layer and pooling layer eliminates the need for a comprehensive connection in many situations. CNNs become well-known deep neural networks when the neurons of the convolution layer are connected to those of the pooling layer. This is primarily due to ConvNets' enormous model size and complex information processing capabilities, which contribute significantly to image recognition tasks. The extraordinary achievements of CNNs in artificial intelligence tasks have substantially boosted the widespread adoption of deep learning methods. Convolutional kernels, which can be thought of as local receptive fields, make up the convolution layer. This characteristic, known as the greatest receptive field (LRF), is one of these networks' primary advantages. During the data processing phase, the convolutional kernels traverse the feature map in order to derive specific feature information. The extracted features are then sent to the aggregating layer for further feature derivation. Eventually, as the data passes through multiple convolutional layers and pooling layers, it reaches the fully connected layer, where the neurons are densely interconnected with the neurons of the upper layers. The data are classified in the fully connected layer using the softmax method, and the resulting values are sent to the output layer as the ultimate output.

Full Convolution Neural Network (FCN): A full convolution neural network is the core of image semantics segmentation. Nowadays, most of the semantic segmentation frameworks are contingent upon FCN. This network first uses convolution to abstract and code the attributes of the input photograph. Next, it slowly re-saves the featured photograph to the dimension of the input photograph through deconvolution or up-sampling [13].

- *U-net:* U-net is a classic FCN structure as well as a generic encoder–decoder system. A layer-hopping connection, which fuses the feature map in the coding phase with that in the decoding phase, is introduced in it for its representation. It is useful for the revival of segmentation specifics.
- *SegNet:* It is also a standard encoder–decoder system. Its property is that the up-sampling process in the decoder leverages the directory of the most time-taking pooling process in the encoder. SegNet is used to segment visible and infrared images into several categories.

2 Literature Review

In this study, we investigated various recent machine learning algorithms for detecting and classifying plant illnesses. These techniques were divided into two categories: machine learning (ML) and deep learning (DL). Furthermore, we carefully assessed

and evaluated the algorithms under consideration, giving our findings in Table 1 for a complete overview.

Dwivedi et al. [14] discovered that current vision methods primarily revolve around either segmenting images or employing feature classification and regression on aerial imagery. For an efficient disease detection approach that requires minimal learning time and possesses remarkable generalization capabilities, an extreme learning machine (ELM) proves to be quite fitting. Notably, L1-ELM has demonstrated superior performance when compared to all existing one-class classification algorithms. It retains optimal learning while simultaneously enhancing generalization [14].

Elfatimi et al. [15] proposed a sophisticated learning system for identifying and categorizing illnesses affecting bean leaves. This method involved combining a publicly available dataset of leaf photographs with a MobileNet model built with the open-source TensorFlow library. Surprisingly, the researchers' proposed model achieved an average classification accuracy of more than 97% on the training dataset and more than 92% on the test dataset. The study included a total of 1296 photographs of bean leaves, with two diseased classes and one healthy class [15].

Dwivedi et al. [16] found that implementing a grape leaf disease monitoring network could be more advantageous than existing methods since it can identify and detect regions impacted by infection or illness. This network's architecture was methodically designed using the faster R-CNN framework. The CA approach was used by the researchers to extract a feature map. They also combined the region proposal network and the feature map to ease multitasking. The proposed disease detection system obtained a remarkable overall accuracy of 99.93% for detecting esca, black rot, and isariopsis [16].

Kumar et al. [17] developed a smart approach to predict powdery mildew, anthracnose, rust, and root rot/leaf blight. A multilayered perceptron (MLP) model classified these disorders. This model outperforms several existing methods in accuracy, according to empirical data. The average disease prediction accuracy approaches 98%. This study also proves this method can detect plant diseases quickly and cheaply [17].

Li and colleagues [18] have devised a novel approach to identify powdery mildew disease (PWD) by employing airborne edge computing and lightweight deep learning methods in tandem with imagery sensors. The incorporation of an unmanned aerial vehicle (UAV) facilitates the efficient and comprehensive survey of forests, significantly reducing the necessity for laborious endeavors. A proposal was put forth to improve the detection process by utilizing a lightweight version of the YOLOv4-Tiny model. The results showed its efficacy in effectively filtering out extraneous images. The study conducted extensive experimentation and found that the proposed system exhibits swift detection with exceptional performance, outperforming other methodologies [18].

Ahmad et al. [19] put forward a useful technique to identify plant disease signs using convolutional neural networks. The PlantVillage dataset has been the focus of past studies, utilizing a progressive transfer learning approach. The proposed

Table 1 Summary of the discussed research papers

Literature reference	Crop culture	Feature selection approach	Classification approach	Datasets	Keywords points	Accuracy (%)	Total references	*Citations received
Elfatimi et al. [15]	Bean leaf	MobileNetV2	Supervised	TensorFlow dataset	MobileNet, TensorFlow, disease classification, beans leaf, deep learning	92–97	22	22
Dwivedi et al. [16]	Grape	R-CNN	Supervised	Benchmark plant datasets	Smart sensing, sensor, agriculture, plant disease, applications	99.93	30	61
Kumar et al. [17]	Green gram	Soil-sensor-based prediction system	Supervised	Sansor dataset	Multi-label classification, Soil-based sensors, artificial neural network, plant diseases	98	58	25
Li et al. [18]	Pine trees	YOLOv4-Tiny	Supervised	8860 images	Pine wilt disease, lightweight deep learning, remote sensing, two-stage detection, airborne edge computing	–	34	21
Ahmad et al. [19]	PlantVillage and pepper	CNN	Supervised	PlantVillage and pepper	Internet of Things, convolutional neural networks, image classification, MobileNet, disease detection, transfer learning	99 and 99.69%	31	31

(continued)

Table 1 (continued)

Literature reference	Crop culture	Feature selection approach	Classification approach	Datasets	Keywords points	Accuracy (%)	Total references	*Citations received
Khattak et al. [20]	Citrus fruit	CNNs	Unsupervised	Citrus and PlantVillage datasets	Citrus fruit diseases detection, deep learning, citrus leaf diseases, convolutional neural network	94.55	42	27
Huang et al. [21]	Peach	Asymptotic non-local means and PCNN-IPELM	Supervised	30,659 images	Extreme learning machine, peach disease detection, asymptotic non-local means, particle swarm optimization, parallel convolution neural network	85–91	44	21
Yang et al. [22]	Tomato	Self-supervised collaborative multi-network	Self-supervised	PlantVillage dataset of 16,486 images	Self-supervised, fine-grained visual categorization, tomato diseases, multi-network	99.7	63	24
Gadade and Kirange [23]	Tomato leaves	LDA, KNN, SVM, Naïve Bayes, decision tree classification	Supervised	PlantVillage dataset of 3000 images	Classification, linear regression analysis, KNN, SVM, tomato leaf disease detection, segmentation	–	10	17
Khan et al. [24]	Apple	GA	Supervised	PlantVillage dataset	Symptoms enhancement, symptoms segmentation, feature extraction, optimal features, recognition		35	131

(continued)

Table 1 (continued)

Literature reference	Crop culture	Feature selection approach	Classification approach	Datasets	Keywords points	Accuracy (%)	Total references	*Citations received
Singh et al. [25]	Mango leaves	Multilayer convolution neural network	Unsupervised	1070 images of mango leaves	Image classification, plant pathology, convolutional neural network, precision agriculture	97.13	29	220
Jiang et al. [26]	Apple leaves	CNNs, GoogLeNet	Unsupervised	26,377 images of apple leaves	Deep learning, convolutional neural networks, feature fusion, apple leaf diseases, real-time detection	78.8	43	426
Devi et al. [27]	Banana	IOT, RFC- GLCM	Supervised	Banana dataset	Hill banana plant, environmental parameters, Raspberry Pi 3, IoT, wireless sensor network, disease detection, RFC	99	7	21
Khitthuk et al. [28]	Grape leaves	GLCM, TFE	Supervised	Grape leaves dataset	Plant leaf disease detection and classification, gray-level co-occurrence matrix, simplified fuzzy ARTMAP	90	10	29

(continued)

Table 1 (continued)

Literature reference	Crop culture	Feature selection approach	Classification approach	Datasets	Keywords points	Accuracy (%)	Total references	*Citations received
Sardogan et al. [29]	Tomato leaves	CNN, LVQ	Unsupervised	500 images	Leaf disease detection, leaf disease classification, convolutional neural network (CNN), learning vector quantization (LVQ)	–	15	312
Chouhan et al. [30]	Plant leaves	Bacterial foraging optimization based radial basis function neural network (BRBFNN)	Supervised	270 images	Bacteria foraging algorithm, image segmentation, plant diseases, radial basis, function neural network, soft computing		26	229
VijayaLakshmi and Mohan [31]	All plant leaves	GLCM and the LBP, FRVM	Supervised	ICL leaf dataset	Plant leaf detection, cellular automata filter, Haralick texture feature extraction, kernel-based particle swarm optimization (PSO), fuzzy-relevance vector machine (FRVM) classification	99.9	31	98

(continued)

Table 1 (continued)

Literature reference	Crop culture	Feature selection approach	Classification approach	Datasets	Keywords points	Accuracy (%)	Total references	*Citations received
Zhou et al. [32]	Rice plant	Fractal Eigenvalues and FCM	Unsupervised	Images of the rice stem	Rice plant-hopper, image process, infestation area, fractal-dimension value, fractal Eigenvalue, rice stem, fuzzy C-means (FCM)	63.5	27	42
Huang [33]	Areca nut	Detection line (DL) technique	Supervised	Areca nut images	Areca nut, neural network, machine vision	90.9	19	61
Al Bashish et al. [34]	All	K-means, GLCM	Supervised	All crops	K-means, segmentation, leaf diseases, stem diseases neural networks	93	10	320

* As per google scholar—accessed on 6.4.2023

system has obtained 99 and 99.69% precision on Pepper and PlantVillage datasets, respectively [19].

Khattak et al. [20] suggested an integrated convolutional neural network model for citrus fruit diseases. The suggested CNN model aims to distinguish between healthy fruits and leaves and those affected by common citrus diseases such as black spot, canker, scab, greening, and melanose. The CNN model has a test accuracy of 94.55%, making it a powerful tool for citrus fruit and leaf disease classification [20].

Huang et al. [21] presented a new method for detecting peach diseases. This method utilizes the asymptotic non-local means (ANLM) image algorithm and integrates a parallel convolutional neural network (PCNN) with an extreme learning machine (ELM) for improved accuracy. The study analyzed a significant dataset comprising 25,513 images and demonstrated noteworthy detection accuracies for diverse peach diseases. The study reported the attainment of the highest accuracies for various peach diseases, namely brown rot, black spot, anthracnose, scab, and normal peach, which were recorded at 89.02%, 90.56%, 85.37%, 86.70%, and 89.91%, respectively [21].

Yang et al. [22] suggested a new model known as LFC-Net, which included three techniques such as location network, feedback network, and classification network. A self-supervision technique for detecting informative areas in tomato images was also presented. A region of interest (ROI) was detected in the tomato image using the initial algorithm, and the subsequent algorithm was assisted in optimizing the iterations under the guidance. Afterward, they utilized the informative regions and the entire image of the tomato. They utilized informative regions and the entire image of the tomato in the last algorithm to classify the diseases from the plant images. The suggested model performed well on the tomato dataset and offered an accuracy of 99.7% [22].

Gadade and Kirange [23] constructed a method for automatically segmenting diseased areas. The segmented region was subjected to an analysis to classify the disease and compute its severity. They put forward a method to detect the leaf disease in which the images were preprocessed, and segmented, attributes were extracted, and the disease was classified. They considered various metrics, namely color, texture, and shape, to analyze the efficacy of the constructed approach. The constructed approach motivated the farmers to implement the automated system to detect the disease occurring on the tomato plant and to measure its severity level [23].

Khan et al. [24] developed a novel method for finding and diagnosing illnesses in apples. Preprocessing, spot segmentation, feature extraction, and classification were the processes in the procedure. The proposed methodology was tested using four types of apple diseases: healthy leaves, black rot, rust, and scab. Notably, effective pre-processing was critical in extracting salient features, resulting in significant accuracy during classification [24].

Singh et al. [25] proposed a multilayer convolutional neural network (MCNN) as a solution for classifying anthracnose fungal disease in mango leaves. They were motivated by the growing popularity of computer vision and deep learning techniques in identifying fungal illnesses, and they set out to create an efficient and dependable method for diagnosing the disease and its symptoms. The results showed that their

system beat other strategies in correctly diagnosing the condition. Their algorithm's accuracy was calculated to be an amazing 97.13% [25].

Jiang et al. [26] proposed an advanced deep learning system for detecting apple leaf illnesses in real-time using improved convolutional neural networks (CNNs). They suggested a novel model for apple leaf disease detection using deep CNNs by combining the GoogLeNet Inception structure and Rainbow Concatenation. They demonstrated that the INAR-SSD model obtained 78.80% mean average precision (mAP) detection performance on the apple leaf disease dataset (ALDD) while retaining a high detection speed of 23.13 frames per second (FPS) [26].

Devi et al. [27] have achieved a detection accuracy of approximately 99% with their proposed illness detection system. The system employs image processing and IoT to extract textural information from photographs of plants. Temperature/humidity sensors and soil moisture sensors are used to measure disease and infection rates in hill banana plants [27].

Khitthuk et al. [28] demonstrated a system for diagnosing plant leaf diseases using color images and an unsupervised neural network. The technology produced outstanding results, with an accuracy rate of more than 90%. Furthermore, the suggested method demonstrated the ability to successfully diagnose many forms of plant diseases. Four different types of grape leaf disease photographs were used to assess the system's categorization ability [28].

Sardogan et al. [29] developed a technique for detecting and categorizing tomato leaf illnesses that combines a convolutional neural network (CNN) model and the learning vector quantization (LVQ) algorithm. They demonstrated the efficiency of the proposed strategy in precisely diagnosing four unique forms of tomato leaf diseases through trials. The dataset used in this analysis included 500 photographs of tomato leaves with indications of various illnesses [29].

Chouhan et al. [30] introduced a technique named "bacterial foraging optimization based on radial basis function neural networks" (BRBFNN) for the automated recognition and categorization of plant leaf illnesses. To assign the optimal weight to a radial basis function neural network, they used bacterial foraging optimization, which further boosts the accuracy and speed of the network to detect and classify the areas affected by different diseases on the plant's leaf. Also found that the region-growing algorithm searched and grouped the seed points with common attributes to maximize the efficacy of the constructed technique. It was observed that the accuracy of the constructed technique was superior in recognizing and classifying the diseases [30].

VijayaLakshmi and Mohan [31] presented a method for the classification of leaves based on their texture, shape, and color characteristics. The primary purpose of the proposed FRVM classification is to reliably predict the kind of leaf from the leaf photos provided as input. The experimental analysis yielded improved values for precision, sensitivity, and specificity of 99.87%, 99.5 and 99.9% compared to the literature, which has been demonstrated by him [31].

Based on visible images, Zhou et al. [32] developed an algorithm that uses fractal eigenvalues and fuzzy C-means to detect stress in rice production induced by RPH infestation. The results proved the algorithm's capacity to discriminate places where

RPH accumulates and identify moldy grey spots on rice plant stems caused by RPH damage. The accuracy in distinguishing these four groups achieved 63.5%, which is expected to meet the needs of practical rice production [32].

Huang [33] adopted a detection line (DL) technique to segment the flaws of betel nut diseases or bugs. The classification was performed using six geometrical attributes, three color properties, and the defective region. This work categorized the quality of the betel nuts using back-propagation neural network (BPNN) classification architecture. The method introduced a work efficiency of 90.9% accuracy in the classification of betel nuts [33].

Al Bashish et al. [34] created an image-processing-based solution for detecting leaf and stem illnesses, with the goal of providing a quick, cost-effective, and accurate method. According to the findings, relying entirely on visual inspection by professionals to identify certain diseases can be costly, especially in underdeveloped countries. The team created a neural network classifier that used statistical classification to correctly detect and categorize the tested diseases with a precision rate of roughly 93% [34].

3 Results and Discussion

The application of machine learning to the process of diagnosing diseases that can be found in crops is currently one of the most important parts of modern agriculture. Never before has it been more vital to rapidly identify illnesses and put a halt to the spread of such ailments. Conventional procedures are insufficient for determining the degree of the sickness since they rely on visual inspection. This is because conventional methods rely on visual inspection. Machine learning has the ability to diagnose a wide variety of crop illnesses, which would significantly reduce the likelihood of experiencing crop losses. The purpose of this paper is to provide an overview of various disease categorization strategies that can be utilized for the identification of plant leaf diseases. The algorithms and methodologies were tested on a number of different species, including the grape, the bean, the green gram, the pine tree, the pepper, the citrus fruits, the peach, the tomato leaves, the mango, the banana, the apple, the paddy, and the areca nut. This ultimately resulted in the collecting and naming of related illnesses that affect these plants.

4 Conclusion

The efficiency of algorithms in the detection and categorization of leaf diseases is demonstrated by the fact that the best results could be obtained with relatively little effort expended in the computing of data. Putting these methods to use has a number of advantages, one of which is that it enables the early or preliminary diagnosis

of plant diseases. It is possible to improve the recognition rate of the classification process by utilizing several methods and hybrid algorithms.

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